Developing an Instrument to Measure Engineering Education Research Self-Efficacy

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Abstract

This research paper focuses on the design and development of a survey instrument to measure engineering education research self-efficacy (EERSE), or the self-perceived ability to conduct research in the area of engineering education. A total of 28 items were initially written to measure this construct along three dimensions: general research tasks such as synthesizing literature and presenting research findings at a conference (12 items), quantitative research tasks such as designing a survey instrument and choosing an appropriate statistical technique for data analysis (7 items), and qualitative research tasks such as creating an interview protocol and describing patterns seen across a set of interviews (9 items). The instrument was electronically administered in the spring of 2019 to three groups: (1) U.S. faculty members who conduct EER, (2) U.S. graduate students enrolled in engineering education doctoral programs, and (3) Indian faculty members who are new to but interested in conducting EER.

An exploratory factor analysis revealed three factors along the expected general, quantitative, and qualitative research dimensions. Cronbach's alpha for the three dimensions ranged between 0.81 and 0.88, indicating high internal consistency between the items. The U.S faculty members reported higher self-efficacy related to performing general research tasks than both U.S. graduate students and Indian faculty members did. They also reported higher self-efficacy related to performing qualitative research tasks than Indian faculty members did. There were no differences in self-efficacy related to performing quantitative research tasks among the three groups.

Practically speaking, this instrument has the potential to be helpful for evaluating the efficacy of trainings and workshops focused on increasing the EERSE of faculty and students. Engineering education researchers can also use this instrument as a tool to self-reflect on their research capabilities.

Introduction

The study of engineering education research (EER) is becoming more prevalent, as evident by the increasing number of scholarly conferences [1] and journal [2] papers focused on engineering education being published each year. EER is relatively well established in countries such as the United States, Sweden, and Israel, all of which have multiple universities that offer bachelors, master's, and/or doctoral degrees in engineering education [3]. They also have large numbers of faculty members, graduate students, and researchers who conduct EER from disciplines as varied as engineering, education, psychology, communications, linguistics, math and learning sciences, technology, physics and chemistry [4].

By contrast, EER is growing but still nascent in other parts of the world such as India, Colombia, South America, and Malaysia. These countries have just begun recognizing EER as an important area of study within the last decade and thus have very few to no formal training programs in engineering education [3]. Nearly all researchers of engineering education in these spaces are trained in traditional engineering research methods rather than in EER methods [5-6]. Borrego [5] states that EER is fundamentally different from engineering research because it necessitates additional considerations of transferability, theoretical frameworks, measurement, and research approaches, all of which can involve a high degree of subjectivity and require more justification of research decisions. Perhaps relatedly, EER papers emerging from these countries have been somewhat slower to adopt the same methods and standards as those published in countries with a better-established foothold in the EER field, more closely resembling scholarship on teaching and learning than basic research [7]. For example, a pilot study conducted by the first author found that even though the number of EER-related publications generated in India has increased, many of these publications lack the basic elements of a research paper such as an identified gap in the literature, research questions, a theoretical framework, and a discussion section. Continued expansion of EER internationally is desirable because it allows for greater sharing, dispersion, and adoption of both pedagogical ideas and research methods. However, more work is necessary to measure, understand, and enhance the readiness of engineering faculty and students to conduct EER around the globe. The current paper begins to accomplish this goal through the development and validation of an instrument to measure engineering education research self-efficacy (EERSE). The EERSE instrument will aid institutions in providing the resources, trainings, and workshops necessary to produce faculty, graduate students, and researchers who can conduct high quality EER-based research. Individual researchers can also use the instrument to self-assess their own capabilities in conducting EER.

The literature suggests a direct relationship between scholarly productivity and research self-efficacy in general, especially among faculty members [8-9]. Scholarly productivity is beneficial not just for individual researchers, but for the broader research community as well because it advances the existing knowledge space [10]. Many institutions expect their faculty members to conduct research related activities [11], as evident by the weight often placed on research productivity in faculty hiring, tenure, and promotion decisions [12]. Increasing the self-efficacy of faculty members and graduate students to conduct EER may encourage more scholars to pursue EER as a viable path for research productivity. Building capacity for doing EER has the potential, in turn, to increase the amount of high-quality, rigorous research being conducted in the field.

Prior Work on Research Self-Efficacy

While no instrument for EERSE currently exists, multiple efforts have been undertaken to measure research self-efficacy in general [13-20]. These measures typically describe research as being comprised of the conceptualization of a study; a literature review; the design and implementation of the study; data collection, analysis, and interpretation; writing and the presentation of the results. Notably, however, the vast majority of this research focuses exclusively on the research self-efficacy of students participating in graduate or undergraduate research. These studies also do not include engineering or engineering education students, with a few exceptions [18-20].

Instruments to study the research self-efficacy of faculty members exist but have limitations [21-23]. Griffioen and colleagues [21] is one such example; they defined research self-efficacy fairly comprehensively, as the steps involved in a research process, but the participants in this study were lecturers with significant research responsibility in a non-university higher education setting. Another study demonstrated that research self-efficacy increases with higher levels of education; however, the items used in this study were not comprehensive and did not cover all aspects of research conduct, for example, synthesizing the literature, collecting and analyzing data, and presenting research findings.

In a study with aim to investigate the relationship between the research self-efficacy and research productivity of faculty members, the researchers, Pasupathy and Siwathu [9], used three scales: general research self-efficacy (confidence in one's ability to design, conduct and publish on a study in the social and behavioral sciences), quantitative research self-efficacy (confidence in one's ability to carry out tasks associated with a quantitative research study such as creating surveys and conducting statistical analyses), and qualitative research self-efficacy (confidence in one's ability to carry out tasks associated with a qualitative research study such as collecting data through interviews, observations, and focus groups and coding the data). The elements of research used in this study include most of the components needed to measure EERSE, but more evidence is needed to support its use with EER researchers, including those coming to the field from traditional engineering disciplines.

Most of the existing instruments for research self-efficacy do not include all the tasks (general, quantitative, and qualitative research tasks) that could be involved in EERSE. Pasupathy and Siwathu's work [9] represents one notable exception; however, more evidence of validity and reliability would be needed to support its application to EER. This study addresses the limitations of previous research related to research self-efficacy by developing a survey instrument to: (1) measure engineering education research self-efficacy (EERSE), an individual's self-belief in their ability to conduct EER scholarship, and (2) collect evidence of its appropriateness for use with three distinct populations: U.S. faculty members who conduct EER, U.S. graduate students who conduct EER, and Indian faculty members who conduct EER. These three groups were chosen because they enable comparison between one experienced group of EER researchers (the U.S. faculty members) and two novice groups (the U.S. graduate students, who are just beginning their formal training in EER, and the Indian faculty, for whom formal EER training has been less readily available).

Self-Efficacy Theory

Self-efficacy is the belief in one's ability to take up a task and successfully complete it [24]. Research self-efficacy, correspondingly, is an individual's beliefs in their ability to successfully complete all the tasks involved in a research project, from selection of a research problem to the reporting of findings in a research manuscript [25]. EERSE is research self-efficacy within the domain of EER, specifically. According to self-efficacy theory, higher levels of task self-efficacy lead to increased motivation and performance in completing that task [24]. Better understanding of EERSE among those who conduct EER can assist in motivating them to grow their EER skills and knowledge, continue their EER efforts, and eventually be successful in achieving EER productivity [9, 23].

Self-efficacy theory also states that self-efficacy is influenced by many factors such as performance accomplishments, vicarious experiences, verbal persuasion, and physiological feedback [24]. Performance accomplishments are experiences (positive or negative) that an individual has had in the past. Individuals who do well on a task will be more likely to believe they can perform well on a similar, future task. Contextualizing this in the current study, research self-efficacy has been shown to rise with an increasing number of years of training and involvement in research activities [15, 21]. An individual's EERSE is therefore expected to increase with an increasing number of years conducting EER, and an increasing number of grants awards, projects completed, and papers published related to EER. Engagement with an engineering education department or center for teaching and learning on campus could similarly increase EERSE as individuals may be receiving EER related training and mentorship in the utilization of these resources. Thus, this paper not only presents a survey instrument to measure EERSE, but compares the EERSE of U.S. faculty members, U.S. graduate students, and Indian faculty members who conduct EER to provide evidence of convergent validity. It is hypothesized that: (1) faculty members who conduct EER will have greater EERSE than graduate students who are still being trained in EER methods, and (2) the average faculty member conducting EER in a country with a well-established EER community will have higher EERSE than the average faculty member conducting EER in a country where EER is still nascent.

Methods

The design and administration of the EERSE instrument was completed in the following stages [26-28]: (1) creation of the survey items, (2) consultation with experts and potential participants to collect evidence of content and face validity, respectively, (3) deployment of the survey to the target populations, (4) data pre-processing, including the deletion of cases with mostly missing data, (5) exploratory factor analysis, and (6) non-parametric Kruskal-Wallis analyses comparing the EERSE of U.S. faculty members, U.S. graduate students, and Indian faculty members who conduct EER.

Item development

Twenty-eight items were written to measure EERSE: 12 items for related to general research tasks, seven related to quantitative research tasks, and nine related to qualitative research tasks. A couple items were adapted from the literature; for example, "I am confident in my ability that I can select a research topic for study" and "I am confident in my ability that I can synthesize current literature related to a research topic" [16, 25]. Other items were newly created for the current study, such as, "I am confident in my ability that I can minimize the researcher bias when interpreting qualitative findings", and "I am confident in my ability that I can ensure data collection is consistent for a sample of participants". The participants were asked to rate their confidence in their ability to perform these tasks using a 5-point, bipolar Likert-type scale with response options (1) strongly disagree (2) disagree (3) neither agree nor disagree (4) agree (5) strongly agree.

Evidence of content and face validity

Evidence of content validity for the EERSE instrument was gathered by subjecting its items to review by experts. Four engineering education faculty members assessed the clarity, relevance and appropriateness of the items in the survey to EER; two faculty members had expertise in quantitative EER methods, one faculty member had expertise in qualitative EER methods, and one faculty member had expertise in mixed EER methods. Evidence of face validity for the instrument was then gathered by asking three students in an engineering education Ph.D. program to take the survey and comment on the item's clarity and wording. Based on the feedback received by the four content experts and three potential participants, some survey items were revised to improve clarity and achieve full construct representativeness.

Data collection procedures

The target population for this study was U.S. and Indian faculty members who conduct EER, and U.S. graduate students who conduct EER. U.S. faculty members and graduate students were recruited to the study by collecting email addresses through engineering education doctoral program websites and by using the contacts of the faculty member advising this research. Indian faculty members were recruited to the study by first identifying a single point of contact (SPOC) at each of 13 Indian institutions and, through these SPOCs, collecting the email addresses of potential participants. An invitation to complete the online EERSE instrument was emailed to all potential participants in the spring of 2019. Participants were asked to respond to the 28 EERSE items, shown in a randomized order irrespective of their corresponding EERSE dimension to avoid bias in their responses. Additionally, faculty were asked a series of questions about: (1) their demographic characteristics, including their gender, country of residence, type of highest degree earned, field of highest degree earned, current academic rank, and current academic department; (2) their EER experiences, including number of years of conducting EER and number of research grants awarded, research projects completed, and conference and journal papers published related to EER; and (3) whether they engaged with an engineering education department and/or center for teaching and learning on their campus. Graduate were asked about their gender and EER-related experiences only. Two follow-up reminder emails were sent to the participants to complete the survey. Graduate students were invited to enter a random drawing for two $25 Amazon gift cards at the end of the survey as an incentive to maximize their participation.

Data pre-processing

Participants who were missing data for at least half of all EERSE items were deleted from the dataset. Missing data on the EERSE and EER experience questions were statistically more likely to come from Indian faculty member participants than from U.S. faculty member or U.S. graduate student participants. Hence, the missing data on these items was handled using group median substitution in which missing data for Indian faculty members, U.S. faculty members, and U.S. graduate students were imputed with the median value for their respective group on that variable. Missing responses on each categorical demographic variable were recoded into the "other" category for that variable. The inter-item correlations for each hypothesized dimension (general, quantitative, and qualitative EERSE) were checked to ensure all items within a dimension were significantly correlated with one another. The Bartlett's test for sphericity was used to determine the suitability of the EERSE items for factor analysis ($p<0.05$) and Kaiser-Meyer-Olkin measure of sampling adequacy (KMO) was used to indicate whether the extracted factors would account for a meaningful amount of variance (KMO>0.8) [28].

Exploratory factor analysis

Exploratory factor analysis (EFA) was conducted on the collected data to examine the fundamental factor structure underlying the EERSE survey instrument and to determine the items belonging to each EERSE dimension. The factors were extracted using principal axis factoring (PAF) because it allows and accounts for the possibility of measurement error when conducting self-report research [28]. The promax with Kaiser normalization method of rotation was used with standard kappa (kappa = 4) because it accommodates correlation between factors, which was suspected to be likely in this analysis. (I.e., that having high self-efficacy along one dimension of EER might be correlated with also having self-efficacy in other EER dimensions. Scree plots, Kaiser's criterion, and parallel analysis were used to determine the number of factors to extract from the data [28]. Items that had low loadings on all factors (<0.4) or cross loadings on at least two factors (>0.3) were removed from the factor structure, and this process was repeated until there were no low- or cross-loading items remaining [28]. Once the factor structure for the EERSE scale was finalized, the internal consistency reliability for each dimension of EERSE was calculated using Cronbach's alpha (α>0.8 preferred) [27]. The final scales for each factor were created by averaging all the item scores associated with that factor.

Kruskal-Wallis analyses

The non-parametric Kruskal-Wallis test was used to compare the EERSE of Indian faculty members, U.S. faculty members, and U.S. graduate students who conduct EER because the EERSE scores for some groups were found to be non-normal. Post-hoc pairwise tests were conducted in the event of a statistically significant difference among groups ($p<0.05$), to understand whether: (1) faculty members who conduct EER will have higher EERSE than graduate students who are still being trained in EER methods, and (2) faculty members who conduct EER in the U.S., where EER is relatively well established as an academic field, have higher EERSE than faculty members who conduct EER in India, where EER is still emergent.

Results

Participants

A total of 218 participants responded to the survey. The survey was distributed to approximately 200 U.S. graduate students, 200 U.S faculty members, and 200 Indian faculty members. The final sample after data cleaning included 180 participants, among them 51 faculty members from 13 institutions in India (approximately 26% response rate), 66 faculty members from 27 institutions in the U.S. (approximately 33% response rate), and 63 graduate students from 9 institutions in the U.S. (approximately 32% response rate). Table 1 provides the demographic information collected from the U.S. and Indian faculty members. Most Indian faculty members who responded to the survey were male (65%), had master's degrees as their highest degree type (73%), had engineering degrees as their highest degree field (82%), and were employed in engineering departments (73%). By contrast, U.S. faculty member respondents were more likely to be female (58%), to have Ph.D. degrees (95%), and to have earned those degrees in engineering education (33%). They were also more likely to work in engineering education programs and departments (52%) than in engineering programs or departments (33%). Sixty percent of the U.S. graduate students who responded to the survey were female, and every graduate student was pursuing a Ph.D. related to the engineering education field.

Table 2 summarizes the EER experiences of the respondents, with information about the number of years they had been conducting EER, as well as their number of EER-related research grants awarded, research projects completed, and conference and journal papers published to date. U.S. faculty member respondents tended to have more than triple the number of years of experience in conducting EER and double the number of research projects completed, compared to Indian faculty member ($p<0.001$, for both) and U.S. graduate student respondents ($p<0.001$, for both). Only U.S. faculty member respondents reported winning EER grants. Their number of EER-related conference papers presented were five and eight times higher than those presented by Indian faculty members and U.S. graduate students, respectively ($p<0.001$, for both). However, both U.S. faculty member ($p<0.001$) and Indian faculty member respondents ($p<0.001$) published more EER-related journal publications than U.S. graduate student respondents, although the number published by U.S. and Indian faculty members differed significantly (*p<0.015*) as well.

Table 1 Demographic characteristics of the faculty respondents

Category	Indian faculty		U.S. faculty	
	n	%	*n*	%
Total	51	100	66	100
Gender				
Male	33	65	26	39
Female	15	29	38	58
Others	3	6	2	3
Type of highest degree				
PhD	10	20	63	95
MS	37	73	2	3
BS	1	2	0	0
Others	3	6	1	2
Highest degree type earned				
Engineering education	6	12	22	33
Engineering	42	82	29	44
Others	3	6	15	23
Current academic program or department				
Engineering Education	12	24	34	52
Engineering	37	73	22	33
Others	2	4	10	15

Note: Percentages may not add up to 100% due to rounding.

Table 2 Engineering education research (EER) related experience of the respondents

Category	Indian Faculty $n = 51$	U.S Faculty $n = 66$	U.S. Graduate Students $n = 63$	Kruskal-Wallis H test
	Mdn (IQR)	Mdn (IQR)	Mdn (IQR)	*p*-value
Experience in conducting EER (in years)	3.0 (2.0)	10.0 (6.5)	3.0 (2.0)	<0.001***
Number of EER grant proposals awarded	0.0 (0.0)	4.0 (6.0)	0.0 (0.0)	<0.001***
Number of EER projects completed	2.0 (0.0)	5.0 (6.25)	2.0 (2.0)	<0.001***
Papers presented in EER conferences	5.0 (3.0)	25.0 (40.0)	3.0 (3.0)	<0.001***
Papers published in EER journals	4.0 (2.0)	6.5 (11.0)	1.0 (0.0)	<0.001***

Note: * *p<0.05*, ** *p<0.01*, *** *p<0.001*

Exploratory factor analysis

The Bartlett's test for sphericity revealed the suitability of the EERSE items for factor analysis (*p<0.001*), and the Kaiser-Meyer-Olkin measure of sampling adequacy (KMO) showed that the extracted factors would account for a meaningful amount of variance if a factor analysis was conducted (KMO=0.899) [28]. Parallel analysis, Kaiser's criterion, and the scree plot method suggested extracting, respectively, two, five, and three factors from the data. Preacher et. al. [29] suggests the search for the number of appropriate factors to extract is done with an aim to meet the research goal. The authors set out to develop an EERSE instrument with three distinct factors corresponding to General, Quantitative, and Qualitative EERSE. The items within each hypothesized EERSE dimension (General, Quantitative, and Qualitative) were also found to be significantly correlated (*p<0.010*), providing further support for a three-factor item structure. A three-factor item structure was hence selected for further analysis.

Three items – "Identify gaps in currently published research related to a research topic" (General), "Collect observational data" (Qualitative), and "Conduct a focus group discussion for a research study" (Qualitative) – had factor loadings less than 0.4 on all three factors and were removed. Three additional items – "Select a research topic for study" (General), "Formulate research questions for a research study" (General), and "Identify emergent themes from qualitative data" (Qualitative) – cross-loaded onto two factors and were also removed. The first factor of the final, three-factor item structure had a total of ten items, of which seven items described general research tasks and three items described quantitative or qualitative research tasks. The second factor had a total of seven items, of which six described quantitative research tasks and one described general research tasks. The third factor also had seven items, of which five items described qualitative research tasks and two items described general research tasks. Items were deleted if they had a different focus than the other items in that factor. The results were three factors measuring General EERSE (7 items), Quantitative EERSE (6 items), and Qualitative EERSE (5 items), respectively.

The final factor loadings for the three-factor EERSE structure are shown in Table 3, with the loadings for each factor sorted from highest to lowest. The factor loadings for the first factor range from 0.51 to 0.85, the second factor from 0.64 to 0.87, and the third factor from 0.46 to 0.90. The coefficients of internal consistency reliability (Cronbach's α) for the three factors ranged from 0.81 to 0.88.

Table 3 Final factor loadings for the EERSE item structure

Item	Category	F1	F2	F3
	General Research Tasks (Cronbach's α =0.85)			
1	Write a peer-reviewed paper for disseminating findings from a research study	0.85		
2	Present my research findings to an audience at a conference	0.74		
3	Select an appropriate theoretical framework for a research study	0.72		
4	Synthesize current literature related to a research topic	0.67		
5	Select a research site for a research study	0.58		
6	Ensure data collection is consistent for a sample of participants	0.51		
7	Determine an appropriate sample size for a research study	0.47		
	Quantitative Research Tasks (Cronbach's α =0.88)			
8	Establish the reliability of a survey instrument		0.87	
9	Choose appropriate statistical analysis techniques for a research study		0.78	
10	Draw appropriate conclusions from statistical analysis		0.75	
11	Validate the items in a survey instrument		0.74	
12	Address analysis issues arising from missing data in survey responses		0.72	
13	Design survey instruments to collect data		0.64	
	Qualitative Research Tasks (Cronbach's α =0.81)			
14	Conduct an interview for a research study			0.90
15	Create an interview protocol			0.80
16	Establish rapport with a participant during an interview			0.67
17	Create a narrative that describes patterns across a set of qualitative interviews			0.50
18	Select appropriate techniques to analyze qualitative data			0.46

Note. F1 = General Research Tasks, F2 = Quantitative Research Tasks, F3 = Qualitative Research Tasks.

Kruskal-Wallis analyses

Table 4 presents the medians and interquartile ranges of the EERSE items and the General, Quantitative, and Qualitative Research Task constructs for the three groups considered in this study. The results of the non-parametric Kruskal-Wallis analyses comparing the three groups on each item/construct are also shown.

The results of the Kruskal-Wallis analyses suggest there are significant differences in the General ($p<0.001$) and Qualitative ($p<0.001$) EERSE of U.S. faculty members, U.S. graduate students, and Indian faculty members who conduct EER. There are no significant differences, however, in the Quantitative EERSE of these same groups ($p=0.180$).

Post-hoc pairwise tests revealed that the U.S. faculty members who conduct EER tended to have significantly higher EERSE than did the U.S. graduate students ($p=0.003$) and Indian faculty members ($p<0.001$) who conduct EER. The group of U.S. graduate students reported lower self-efficacy than U.S. faculty members, specifically, on selecting a theoretical framework for a research study ($p=0.013$), selecting a research site ($p=0.001$), ensuring consistent data collection across participants ($p=0.036$), and presenting their research findings at a conference ($p<0.001$). Further, the Indian faculty members reported lower self-efficacy than the U.S. faculty members on synthesizing the current literature related to a research topic ($p<0.001$), selecting a theoretical framework for a research study ($p=0.009$), selecting a research site ($p=0.002$), ensuring consistent data collection across participants ($p<0.001$), and disseminating findings in peer-reviewed papers ($p=0.001$). There were, however, no significant differences in the General EERSE of Indian faculty and U.S. graduate students who conduct EER.

U.S. faculty members ($p<0.001$) and U.S. graduate students ($p=0.030$) in the EER field had statistically higher Qualitative EERSE, overall, than Indian faculty members in the EER field. Both the U.S. faculty members and U.S. graduate students reported higher self-efficacy than the Indian faculty members in conducting qualitative interviews for a research study ($p=0.001$, for both) and creating a narrative to describe patterns across a set of interviews ($p<0.001$ and $p=0.019$, respectively). U.S. faculty members also tended to have higher self-efficacy than Indian faculty members in creating an interview protocol and establishing rapport with a participant during an interview ($p<0.001$, for both). There were no significant differences in the Qualitative EERSE between EER U.S. faculty members and EER U.S. graduate students.

Table 4 Descriptive Statistics of EERSE items

#	Items	Indian Faculty $n = 51$	U.S Faculty $n = 66$	U.S. Graduate Students $n = 63$	Kruskal-Wallis H test p-value
		Mdn (IQR)	Mdn (IQR)	Mdn (IQR)	
	General Research Skills	4.0 (0.6)	4.5 (0.9)	4.0 (0.9)	<0.001 ***
1	Write a peer-reviewed paper for disseminating findings from a research study	4.0 (1.0)	5.0 (1.0)	4.0 (1.0)	0.001 **
2	Present my research findings to an audience at a conference	4.0 (0.0)	5.0 (1.0)	4.0 (2.0)	0.001 **
3	Select an appropriate theoretical framework for a research study	4.0 (0.0)	4.5 (1.0)	4.0 (2.0)	0.003 **
4	Synthesize current literature related to a research topic	4.0 (1.0)	5.0 (1.0)	5.0 (1.0)	<0.001 ***
5	Select a research site for a research study	4.0 (0.0)	5.0 (1.0)	4.0 (2.0)	<0.001 ***
6	Ensure data collection is consistent for a sample of participants	4.0 (1.0)	5.0 (1.0)	4.0 (1.0)	<0.001 ***
7	Determine an appropriate sample size for a research study	4.0 (0.0)	4.0 (1.0)	4.0 (1.0)	0.428
	Quantitative Research Skills	4.0 (0.5)	3.8 (1.0)	3.7 (1.3)	0.180
8	Establish the reliability of a survey instrument	4.0 (0.0)	4.0 (2.0)	3.0 (2.0)	0.065
9	Choose appropriate statistical analysis techniques for a research study	4.0 (1.0)	4.0 (1.0)	4.0 (2.0)	0.712
10	Draw appropriate conclusions from statistical analysis	4.0 (0.0)	4.0 (2.0)	4.0 (2.0)	0.919
11	Validate the items in a survey instrument	4.0 (1.0)	4.0 (1.0)	4.0 (1.0)	0.311
12	Address analysis issues arising from missing data in survey responses	4.0 (1.0)	4.0 (1.0)	4.0 (1.0)	0.178
13	Design survey instruments to collect data	4.0 (0.0)	4.0 (2.0)	4.0 (1.0)	0.035 *
	Qualitative Research Skills	4.0 (0.6)	4.8 (0.9)	4.2 (0.8)	<0.001 ***
14	Conduct an interview for a research study	4.0 (1.0)	5.0 (1.0)	5.0 (1.0)	<0.001 ***
15	Create an interview protocol	4.0 (0.0)	5.0 (1.0)	4.0 (1.0)	<0.001 ***
16	Establish rapport with a participant during an interview	4.0 (0.0)	5.0 (1.0)	4.0 (1.0)	<0.001 ***
17	Create a narrative that describes patterns across a set of qualitative interviews	4.0 (1.0)	5.0 (1.0)	4.0 (1.0)	<0.001 ***
18	Select appropriate techniques to analyze qualitative data	4.0 (1.0)	4.0 (1.0)	4.0 (2.0)	0.162

Note: * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Discussion and Implications

An instrument with three dimensions of EERSE corresponding to confidence in performing general, quantitative, and qualitative research tasks was proposed based on a review of the literature, which revealed gaps in existing scales used to measure research self-efficacy. Items were generated for each of these three dimensions, and the content and face validity of these items was checked. An EFA was run on the responses of 180 U.S. faculty members, U.S. graduate students, and Indian faculty members who conduct EER. An 18-item, three-factor item structure emerged, as hypothesized. Non-parametric Kruskal-Wallis analysis of the responses from the three participant groups was performed on each dimension of EERSE to help establish evidence of convergent validity for the instrument. The U.S. faculty members were found to have statistically higher General EERSE than the U.S. graduate students and Indian faculty members sampled. The U.S. faculty members and U.S. graduate students also had higher Qualitative EERSE than the Indian faculty members who participated in the study. There was no statistically significant difference between the three groups on Quantitative EERSE, on which scores were lowest for all three groups.

These findings make sense given that EER is relatively better established in the U.S. than in India [3]. As previously shown, the median number of years' experience conducting EER and the median number of EER-related grants awarded, projects completed, and papers published for U.S. faculty members were all significantly higher than the corresponding median numbers for Indian faculty members in the sample. Furthermore, significantly more U.S. faculty members had highest degrees in engineering education and/or appointments in engineering education departments than did Indian faculty members, who tended to have engineering degrees. It is unsurprising that the Indian faculty members would have similar Quantitative EERSE but lower Qualitative EERSE, as compared to their U.S. counterparts, since most engineers are trained in quantitative tools and analysis, but not in qualitative methods [30]. U.S. faculty members were also more likely than Indian faculty members to have earned a Ph.D. involving a dissertation research project which might explain why they had higher self-efficacy in performing general research tasks.

As with the group of Indian faculty members, the U.S. faculty members significantly outpaced the U.S. graduate students on all experiential measures of EER research. It was, therefore, expected that the U.S. faculty members would also report significantly higher EERSE than the U.S. graduate students, but this was evident for only General EERSE. The lack of a significant difference between U.S. faculty members and U.S. graduate students on Qualitative EERSE is somewhat surprising, as this finding does not align with the published work [30]. Yet, at the same time, this finding and the gap in Qualitative EERSE between U.S. graduate students and Indian faculty members suggest EER programs and departments are succeeding at instilling in students qualitative research methods such as how to conduct, analyze, and interpret interview data. This study suggests the three groups considered in this study are on a spectrum, with Indian faculty members at the beginning, U.S. graduate students in the middle, and U.S. faculty members more at the end. Moving along the spectrum from left to right, an increase in EER exposure and experience leads to an increase in Qualitative and (later) General EERSE. By contrast, Quantitative EERSE appears to lag behind General and Qualitative EERSE and to stay constant over time, potentially indicating a need for more training in this area field-wide. These preliminary results suggest countries and institutions interested in growing their capacity for conducting EER might accomplish this goal by (1) providing resources and training related to proposing, conducting, and publishing EER research, as well as high-quality research in general, (2) making available support to attend and network at EER-related conferences, and (3) establishing EER programs and departments. The EERSE instrument itself could be used for tracking the outcomes of these interventions, to determine how effective participation is at increasing EERSE. Individual faculty members and graduate students interested in improving their EER skills may also find the EERSE instrument to be helpful as a self-reflection tool for identifying areas of potential growth and improvement.

Future Work

This paper presents an instrument for measuring engineering education research self-efficacy (EERSE) and compares the EERSE of three groups who conduct EER: U.S. faculty members, U.S. graduate students, and Indian faculty members; however, these findings also come with limitations and opportunities for further research. The sample considered in this study was not representative of the entire community of engineering education scholars in the U.S and India, nor did it include participation from other countries where EER is well established (e.g., Australia, Sweden, and Israel) and still growing (e.g., Colombia, South America, and Malaysia). Second, some important items related to General and Qualitative EER research tasks fell out of the EERSE factor structure. Exploring whether the same results are obtained with a larger, more inclusive sample of the EER community would be a first step toward further validation of the instrument for use in measuring EERSE among EER researchers, students, and faculty. The results of this study suggest that a five-point Likert scale may not be sufficient to accurately capture and differentiate between EERSE levels; gauging how the validity and statistical results change with a more precise measure (for example, a 7- or 10-point scale) thus seems warranted. Another possible direction for future work could be examining how responses change if participants are asked to rate their General, Quantitative, and Qualitative self-efficacy in the context of engineering education research, specifically. Lastly, the impact on EERSE of other demographic characteristics and EER performance accomplishments [24], such as gender, type and field of highest degree, type of current academic department, and number of years of EER experience, is another ripe area for further investigation.

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